Seeking forward, looking forward: A replication and generalization of the Future Orientation Index based on Baidu Index

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Abstract

Preis, Moat, Stanley, and Bishop (2012) introduced the Future Orientation Index (FOI) via Google Trends to gauge a country's future orientation, measuring how much individuals prioritize the future in their thoughts and actions. Their research found that a higher FOI, marked by greater search interest in the upcoming year compared to the past, correlated with elevated economic success, indicated by higher per capita GDP. Despite its widespread use in cross-cultural studies, due to the evolving nature of the Internet in the past decade, it remains uncertain whether the FOI can still reliably measure future orientation. Our study aimed to replicate and extend correlations between FOI and key development indicators, such as GDP and the Human Development Index (HDI), across countries with different dominant search engines (from Google to Baidu), across time periods (from 2012 to 2021), and across levels (inter-country to intra-country and individual). Our results successfully replicated the findings from Preis et al. (2012): the Baidu-based FOI consistently demonstrated a positive correlation with province-level GDP (r = .719 ~ .860, ps < .001, BF_{10} > 100) and HDI (r = .635 ~ .867, ps < .001, BF_{10} > 100) from 2012 to 2021 in China. However, for exploratory generalization, the FOI did not predict individual-level patience (β = -0.038, p = .402). Our findings, alongside the open dataset of the Baidu-based FOI, provide an easily accessible index and a practical example to investigate intra-cultural differences in future orientation within China. Furthermore, our results underscore two prerequisites for utilizing the FOI as a measure of future orientation in future research: 1) Choose a locally dominant search engine and unambiguous keywords to calculate the FOI, and 2) Apply the FOI within a group-level context rather than an individual-level one.

Keywords: future orientation, future orientation index, Baidu index, GDP, patience

1 Introduction

As a fundamental concept in decision-making, future orientation refers to the extent that an individual's thinking and behavior refers to the future (Gjesme, 1979). Higher future orientation could benefit individuals in many aspects, including more long-term planning and delay gratification (Johnson et al., 2014; Strathman et al., 1994), more academic engagement (Horstmanshof & Zimitat, 2007), less risky behavior (Sansone et al., 2013), and better financial planning (Howlett et al., 2008), etc. At a country level, higher future orientation have been associated with more pro-environment behaviors (Carmi & Arnon, 2014) and a higher national quality of life (for reviews, see Seginer 2009). These associations make future orientation even a key dimension of cultural differences (Hofstede & Minkov, 2010). Considering its importance and benefits, a growing body of research has focused on developing diverse measurements or indexes of future orientation which emphasize both accuracy and validity, e.g., Bearden et al. (2006); Hofstede and Minkov (2010); Zimbardo and Boyd (1999).

Different from these measurements based on seif-report, Preis et al. (2012) innovatively developed the Future Orientation Index (FOI) based on online searching data of countries represented by Google Trends (https://trends.google.com). Practically, the FOI assessed the country-level future orientation by quantifying the extent to which Internet users sought information about the future rather than the past, i.e., the ratio of the volume of searches made for the coming year (e.g., 2024) to the volume of searches for the previous year (e.g., 2022). Comparing the FOI of 45 countries and their per capita GDP, their results showed that countries with higher FOI (seeking more about the future on Google) possess a larger per capita GDP (r = 0.78, Preis et al., 2012). This strong correlation not only provides further evidence for the economic benefits of future orientation at the country level, but also reveals that a country's economic

prosperity can be reflected in the online information-seeking behavior of its citizens. This research garnered tremendous academic and public attention: amassing over 240 citations on Google Scholar (till Jun. 2023) and being featured in prominent media such as *The Guardian* (Sedghi, 2013) and *The Washington Post Times* (Dewey, 2013).

Due to its unique and effortless data source, compared with those traditional assessments solely relying on participants' self-reports, the FOI has several inherent strengths in convenience and effectiveness. Through the freely available data of the Google Trends website, the FOI eliminates the need for administering questionnaires, making it significantly more accessible and cost-effective. By relying on online behavioral indicators from billions of Google users, the FOI exhibits enhanced ecological validity and reduces sampling biases. Thus, FOI has emerged as a widely-utilized measure while investigating the relationship between future orientation and features across various research domains, especially in cross-cultural contexts (Shepard & Turner, 2019): e.g., intertemporal decision preference (Burro et al., 2022), fertility (Cavalli, 2020), income taxes (Petutschnig, 2017), environmental policy performance (Schaub, 2022), etc.

Also due to this convenient data source, the previous studies have directly calculated the FOI from Google Trends without verifying its priori stability or efficacy. After over a decade of use of FOI, it is a right and crucial time for revisiting the replicability and validity of the FOI, especially its correlation with GDP for three key aspects:

1) The stability and generalizability of FOI across countries with different dominant search engines. To our best knowledge, the majority of existing research has primarily relied on Google Trends to calculate the FOI (e.g., Burro et al. (2022); Cavalli (2020); Schaub (2022)). However, Google searching data may fail to cover the trends of citizen's online behavior in certain non-WEIRD countries where Google is not the dominant search engine, such as China with Baidu

as the dominant search engine, Russia with Yandex, South Korea with Naver, etc. These countries also played important roles in the global economy and politics. Taking China as a non-WEIRD example (Henrich et al., 2010), Baidu (instead of Google) is the dominant search engine in China: Baidu holds a commanding 59% share of the Chinese search engine market, with Google accounting for a mere 2% share (StatCounter, 2023). Thus, solely relying on Google Trends data in China to calculate the FOI may introduce substantial sampling bias as well as significant distortions and inaccuracies in FOI. This limitation was particularly evident given the contradiction between different measurements of country-level future orientation data: Measured by questionnaires, China ranks among the *most* future-oriented (i.e., long-term oriented) countries according to Hofstede's Cultural Dimensions Theory (Hofstede & Minkov, 2010); But, measured by FOI, China becomes one of the *least* future-oriented countries (41 out of 45) in Preis et al.'s (2012) study. Therefore, to obtain a more precise and representative FOI in these counties, a more suitable approach would be calculating the index based on local search engines data (e.g., Baidu in China) and subsequently investigating the stability and replicated of FOI, as well as its relationship with GDP, across countries with different dominant search engines different search engines prior to its practical application.

2) The robustness of FOI across time periods. It's crucial to test whether the FOI still predicts economic indicators (e.g., GDP) as reliably across over ten years ago when it was first introduced. Despite a series of methodological advantages of the FOI, the replication crisis could still be a major concern of studies based on online query data (Lai et al., 2017). The dynamic nature of the Internet and the continuously evolving behaviors of online users over time contribute to the uncertainty surrounding the replicability of results derived from such data sources.

3) The generalizability of FOI across levels. It is also valuable to explore the efficacy of the FOI as a comprehensive tool to capture the variations of future orientation across different levels: from inter-country level to intra-country or individual level. Originally proposed as a country-level index, the FOI was mostly utilized to examine variations in future orientation between countries. However, emerging research has shed light on notable differences in future orientation within cultures (Falk et al., 2018) and between individuals (Steinberg et al., 2009). Actually, these cultural heterogeneities within countries can be as significant as or even more significant than inter-country variation (Falk et al., 2018). Recently, increasing studies have attempted to develop indexes to quantify intra-country cultural differences in China. However, the majority of these efforts have primarily focused in the variations on the dimensions of tightness / looseness (Zhang et al., 2023) or individualism / collectivism (Gong, Zhu, Gürel, & Xie, 2021), leaving a deficiency of available resources to capture the multifaceted aspects of future orientation within cultures.

To fill these gaps, the current study conducted a direct replication and exploratory generalization of the original study by Preis et al. (2012). In detail, we calculated the FOI for the 31 provinces in China using a local search engine (i.e., Baidu) and compared the results with Google (across search engines) from 2012 to 2021 (across time periods), and then tested its relationship with the per capita GDP of each province and also individual-level patience (across levels, from inter-country to intra-country and individual).

2 Method

2.1 Data collection

The data collection fell into three parts: Calculation of the FOI, Collection of the province-level data, and Collection of the individual-level data:

2.1.1 Calculation of the FOI

The calculation of FOI followed the original formula proposed by Preis et al. (2012), which is the ratio of the volume of searches made for the coming year (represented in Arabic numerals) to the volume of searches for the previous year. Differently, to test the stability of FOI across search engines, the volume of searches was quantified by Baidu Index (a search index based on the biggest local search engines in China) instead of Google Trend. Take the calculation of FOI for 2018 as an example, the formula should be as follows:

$$FOI_{2018} = \frac{Baidu\ Index\ for\ \text{“2019”}\ during\ 2018}{Baidu\ Index\ for\ \text{“2017”}\ during\ 2018}$$

Then, to show the robustness of FOI across time periods, we obtained the Baidu-based FOI for the past decade. Since the earliest available Baidu Index started in 2011, the FOI was calculated from 2012 to 2021. The year 2013 was excluded as an outlier since the related previous year 2012 was also the name of a famous movie, which may distort the regular pattern (see our Supplementary Materials 6.1). All the data of the Baidu Index across 31 provinces were extracted from https://index.baidu.com. To ensure the Baidu Index is free of typos or mismatch, a separate researcher independently cross-verified all extracted index and made necessary corrections.

2.1.2 Province-level data

Consistent with the previous study (Preis et al., 2012), the GDP per capita was used to reflect the level of economic development across 31 provinces from 2012 to 2021. The data on GDP per capita were collected from the China National Bureau of Statistics (https://data.stats.gov.cn/).

Besides the GDP per capita, we added HDI as a more comprehensive assessment of the development level across provinces. The HDI was defined as an average of achievements in three dimensions: health, education, and standard of living (Klugman et al., 2011). The data on HDI

were collected from the Global Data Lab (https://globaldatalab.org/shdi/) (Smits & Permanyer, 2019). The HDI data were available from 2012 to 2019.

2.1.3 Individual-level data

We used the patience index measure by the Global Preference Survey 2012 (GPS 2012) (Falk et al., 2018; Falk et al., 2022) as our main dependent variable on our individual-level data. The data of Chinese respondents in the GPS 2012 covered 25 provinces in mainland China (N = 2574). All respondents finished the survey from April to May 2012. This public dataset measured a series of economic preferences and was widely used by previous studies investigating the individual difference of patience (e.g., Burro, McDonald, Read, & Taj, 2022; Nieminen, 2022). The patience index combined a quantitative measurement (i.e., five binary choices between an immediate and a delayed payment) and a qualitative measurement (i.e., a self-assessment of willingness to wait). A higher patience index refers the respondent is more patient and more willing to wait. For more reference about this measurement approach, please see Falk et al. (2022).

Considering the potential impact of other variables related to patience, we also controlled respondent's age, gender, risk preference, and math skills as covariates. These covariates were also included in the GPS 2012.

2.2 Data analysis

Our data analysis plan also consisted of three parts: First, the descriptive analysis of Baidu-based FOI was conducted to show the general distribution and inner-culture differences of future orientation between provinces. Then, to test the stability of FOI across search engines at an intra-country level, we tried to replicate the positive correlation between the Baidu-based FOI and the economic development of provinces in China. Moreover, this replication was repeated using the data from the past decade to test whether this correlation was robust across the time period. Lastly,

to generalize the relationship between FOI and city development to individual preference, we tested the predicting effect of FOI on individual-level patience.

All analyses were conducted using R 4.0.3 (R Project for Statistical Computing). The following R packages or functions were used respectively: *lm* and *lmer4* (Bates et al., 2014) for linear (mixed) regression models, *lmrob* of *robustbase* (Maechler et al., 2023) for robust regression models, *ggplot2* (Wickham, 2011) for visualization, and *bruceR* (Bao, 2023) for presenting results. The levels of significance for all analyses were set to 0.05. We also used JASP (Love et al., 2019) and R package *BayesFactor* (Richard et al., 2022) to calculate Bayes factors (BF_{10}) for our main analyses with the default prior. All the raw data (including the FOI, province-level, and individual-level data) and R code for replicating our results were available at https://osf.io/ygj76/?view_only=1d98730f60a04588a987f5d25aa987e9.

2.2.1 Description of the FOI

For the descriptive analysis, we aggregated the FOI from 2012 to 2021 by mean for each province. The five highest-FOI and lowest-FOI provinces were listed respectively. To show the difference of FOI of different provinces geographically, we drew a FOI map. Then, according to the geographic division of China (National Bureau of Statistics, 2020), we tested the regional difference among three regions (i.e., Eastern, Central, and Western[1]) using the linear mixed model with year and city as random intercepts. Besides, to compare the dispersion level of FOI across the latest decade, we also calculated the coefficient of variation (CV) of FOI for each year using the formula $CV = SD / M$.

2.2.2 Predicting province-level GDP/HDI by FOI

[1] Eastern: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; Central: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; Western: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

For each year, the pairwise correlation with FOI and two province-level variables (i.e., GDP per capita and HDI) was tested respectively. In light of the small sample size (i.e., 31 pairs of data points) of the correlation test, the robust regression based on an M-estimator using iteratively reweighted least squares estimation (Field & Wilcox, 2017; Koller & Stahel, 2011) was also conducted as a robust check in addition to the simple correlation. To view the data distribution directly, each correlation between FOI and GDP (or HDI) was accompanied by a scatterplot.

2.2.3 Predicting individual-level patience by FOI

A total of 202 respondents were excluded for age under 18 years or answered incompletely with missing values. After data cleaning, 2372 respondents were valid for future analysis.

We used the hierarchical linear model and a model comparison approach to test the relationship between FOI and individual-level patience. The patience, age, gender, risk preference, and math skills were set as individual-level variables and the FOI (in 2012) was set as a province-level variable. To control the systematic difference of patience between different provinces, the provinces were also set as a random intercept. Following the recommendation of Enders and Tofighi (2007), all the individual-level variables were centered within cluster.

Then, a series of hierarchical linear models were conducted. The Model 1 only included the individual-level predictors (i.e., age, gender, math skills, and risk preference) with the patience index as an outcome. Then to preliminarily investigate the predicting effect of province-level FOI, we tested the correlation between the FOI and the random intercept of each province in Model 1 (Mata et al., 2016). And then, to control the systemaic difference between city, the Model 2 added the FOI as the province-level predictor. For exploration, the Model 3 tried to add the interaction term between the FOI and individual-level predictors. Thus, by comparing the model fitting between the Model 1 and Model 2 (or Model 2 and Model 3), we could reveal whether there is a

significant effect of province-level FOI (or the across-level interaction) on individual-level patience.

3 Results

3.1 Descriptive results of the FOI across provinces

All the FOI for each province from 2012 to 2021 were listed in our Supplementary Materials (Table S1). For the detailed regional difference of FOI and provinces with the highest (or lowest) FOI, please see the Figure 1 for an FOI map.

These observed systematic differences in FOI across provinces showed the intra-cultural variation of future orientation in China. In detail, the Eastern China (e.g., Shanghai, Zhejiang, $M \pm SD = 0.981 \pm 0.136$) had significantly higher FOI than the Central China (e.g., Shanxi, Jilin, $M \pm SD = 0.826 \pm 0.055$, $p = .008$, $BF_{10} = 6.24$) and the Western China (e.g., Tibet, Gansu, $M \pm SD = 0.791 \pm 0.086$, $p < .001$, $BF_{10} > 100$). Besides, the degree of this intra-cultural variation was stable (*CV* ranges from 0.13 to 0.21), without an observable increasing (or decreasing) trend from 2012 to 2021. These results suggested the Baidu-based FOI could be sensitive and stable to catch the intra-cultural variation of future orientation between China provinces.

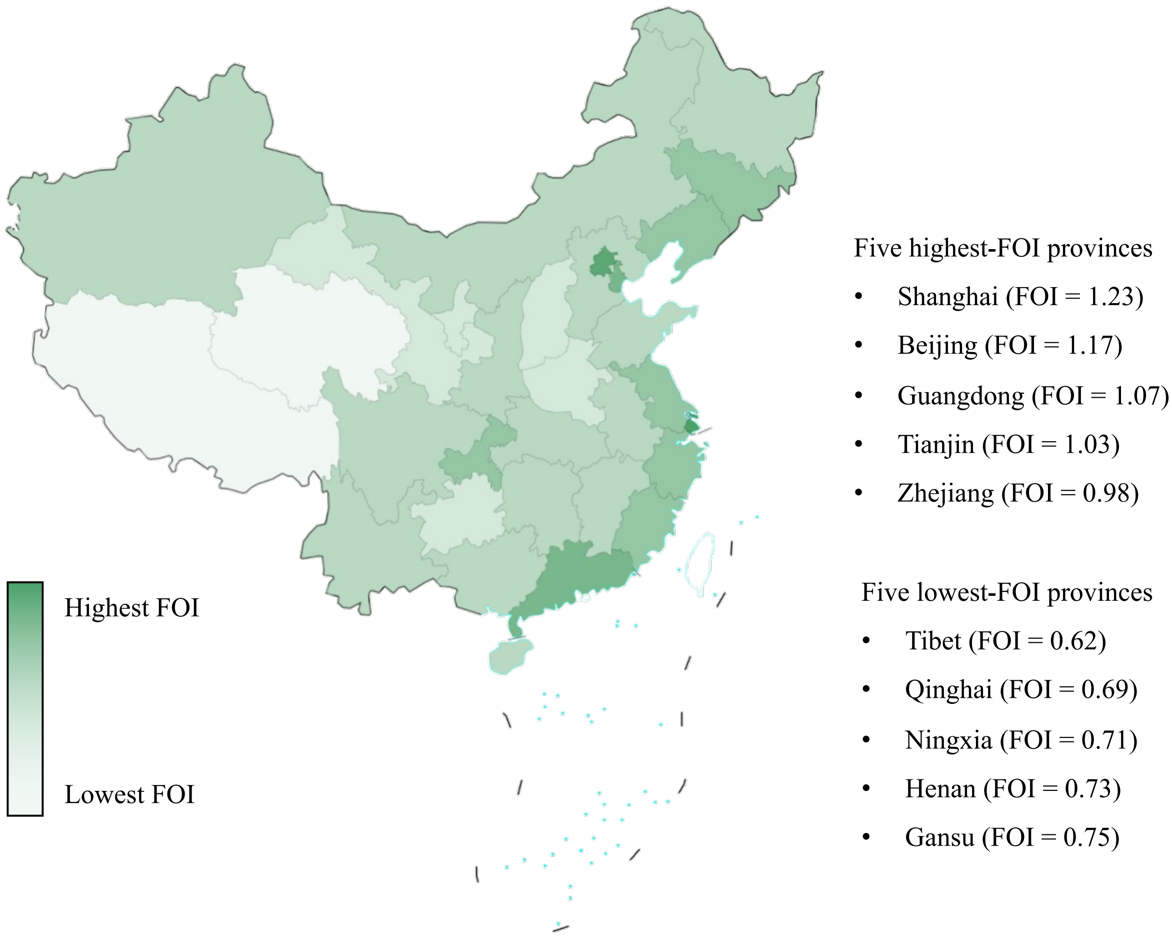

Figure 1. A FOI map of China provinces. The FOI used in this map is aggregated by mean from 2012 to 2021 (exclude 2013) for each province. Deeper/lighter green means a higher/lower FOI. The grey area means not included in this study. The five provinces with the highest/lowest FOI were listed on the right side.

3.2 Predicting province-level GDP/HDI by FOI

From the correlation analysis, the FOI and GDP (or HDI) were highly correlated (detailed see Table 1) through the decade (*ps* < .001, $BF_{10} > 100$, *r* ranging from .72 to .87), suggesting at the province level, a higher FOI was related to a higher GDP and HDP. To check the robustness, the robust regressions also consistently showed a significantly positive relationship between the FOI and GDP (or HDI), suggesting the stability of the correlation results. The year 2019 was taken as an example to plot a visualized scatterplot (Figure 2), and the scatterplots for all other years

were shown in Supplementary Materials (Figure S1 & S2). Consistent with Preis et al. (2012), these results replicated that provinces may benefit from higher FOI, both in its economic development (i.e., GDP) and generalized city development (i.e., HDI).

We also used Google Trends to calculate the province-level FOI, and tested its correlation with GDP / HDI (see our Supplementary Materials 6.4). Consistent with our argument, Google-based FOI in China performed worse on the correlation and result in distortions, e.g., weak correlation with GDP (most of the correlation was not significant, and even *negative* correlation for some years), inexplicable missing values for some provinces. Also taking the year 2019 as an example, the Figure 2 showed that there was significant deviation between the Baidu-based FOI and the Google-based FOI (r = .030, p = .876, BF_{10} = 0.282), and more importantly, the relationship between Google-based FOI and the GDP / HDI is weak (r = .221 / .130, p = .247 / .500, BF_{10} = 0.431 / 0.282) with a much wider error bar. These results highlighted the necessity of utilizing local search engines to calculate an accurate and reliable FOI, rather than relying solely on Google.

Table 1. The relationship between the Baidu-based FOI and GDP/HDI from 2012 to 2021 in China.

Year	Baidu-based FOI and GDP		Baidu-based FOI and HDI	
	Correlation (r)	Robust regression (β)	Correlation(r)	Robust regression (β)
2012	.785	.821	.852	.835
2014	.739	.742	.867	.844
2015	.822	.805	.851	.830
2016	.771	.610	.866	.865
2017	.848	.832	.790	.730
2018	.719	.686	.801	.773
2019	.860	.858	.848	.794
2020	.828	.829	/	/
2021	.749	.678	/	/

Note: r, the correlation coefficients between the Baidu-based FOI and GDP/HDI; β, the standardized regression coefficients from the robust regression using FOI to predict GDP/HDI. All the coefficients were significant at p < .001and with extreme evidence from BF_{10} > 100. The results of FOI and HDI were missing for 2020 and 2021 since the HDI data is not accessible.

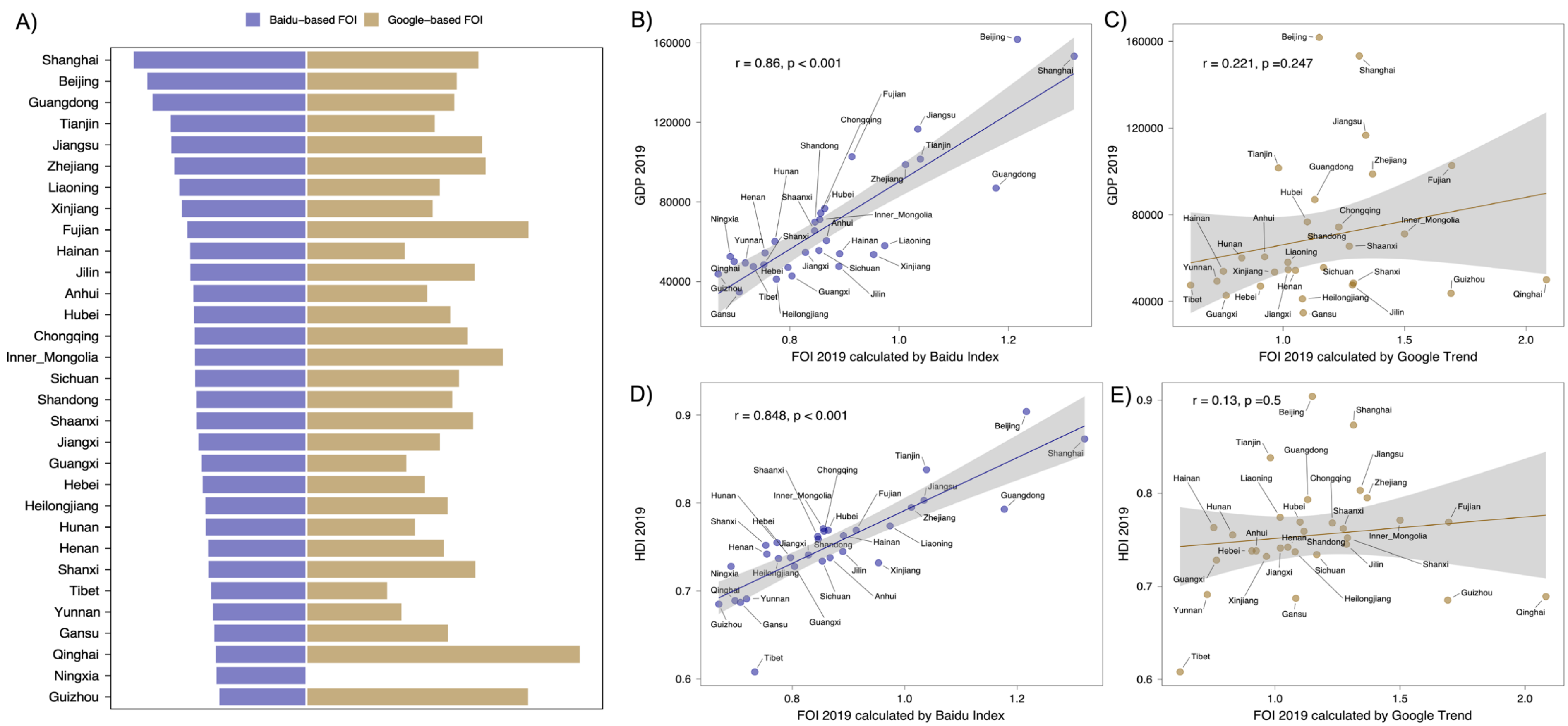

Figure 2. Panel (A): The Future Orientation Index (FOI) of China provinces in 2019 calculated by Baidu Index (blue bar) and Google Trends (yellow bar). The order of the provinces was sorted by Baidu-based FOI. The Google-based FOI for Qinghai province was missing. Panel (B & D): Scatterplots between the Baidu-based FOI and GDP / HDI of China provinces in 2019. Panel (C & E): Scatterplots between the Google-based FOI and GDP / HDI of China provinces in 2019. Each dot represented a province in China and was labelled by the province name. The trendline (blue for Baidu-based and yellow for Google-based) represents the fitted regression line, and the error bar represents the 95% confidence intervals.

3.3 Predicting individual-level patience by FOI

Results from a series of hierarchical linear models did not support the relationship between the FOI and individual-level patience (Table 2). From the Model 1, the results showed that younger age, male, better math skills, and higher risk preference were related to more patience (*ps* < .01). However, the random intercept of each province could not be explained by the province-level FOI (r = - .098, p = .642, BF_{10} = 0.473), suggesting the relationship between the FOI and the patience (aggregated by province) was weak.

Then, after controlling these individual-level variables and adding the FOI as the province-level predictor, the model fitting of Model 2 did not improve with a negligible effect of the FOI on patience (β = -0.020, p = .671). is still weak. As shown in Model 3, the only significant interaction was detected between the FOI and age (β = -0.044, p = .026). However, the effect size and the improvement in model fitting were still too weak to reach a stable conclusion (see the Supplementary Materials 6.5 for detailed simple slope analysis).

These results may reveal one weakness of the province-level FOI: Although the FOI may be linked to province-level GDP/HDI solidly, it's still hard to apply the FOI to the individual level. It should be noted that the FOI may moderate the effect of individual-level factors (e.g., age) on patience, but more research is needed to further test these potential interactions.

Table 2. The relationship between the FOI and individual-level patience (N = *2372*).

Variables		Model 1		Model 2		Model 3	
		β	*SE*	β	*SE*	β	*SE*
Individual-level	Age	-0.076***	0.022	-0.076***	0.022	-0.074***	0.022
	Gender (1 if female)	-0.058**	0.020	-0.058**	0.020	-0.055**	0.020
	Math skills	0.059**	0.021	0.059**	0.021	0.057**	0.021
	Risk preference	0.148***	0.022	0.148***	0.022	0.149***	0.022
Province-level	FOI			-0.020	0.045	-0.040	0.045
	FOI × Age					-0.044*	0.020
AIC		6604.1		6605.3		6601.6	
BIC		6644.5		6651.5		6653.6	

Conditional R^2	.069	.071	.074

Note: $p^{***} < .001$, $p^{**} < .01$, $p^{*} < .05$.

4 Discussion

The primary aim of the present study was to replicate and extend the findings of Preis et al. (2012) by exploring the correlation between the Baidu-based FOI and GDP/HDI at the province level in China, as well as the association between FOI and individual patience at the individual level. Our study consistently suggested that: 1) The correlation between FOI and GDP reported in Preis et al. (2012) is replicable across different search engines (from Google to Baidu); 2) The positive correlation between Baidu-based FOI and GDP is stable across time period (from 2012 to 2021); 3) The validity of Baidu-based FOI is potentially across different levels: from inter-country to intra-country level, but not to individual level. These results showed the robustness and stability of FOI as a convenient tool to quantify the future orientation at a country/province level, and also highlighted the necessity to calculate FOI based on a local dominant search engine (but not always Google).

Despite the seemingly simple and straightforward calculation of the FOI (solely based on the ratio of two search indices), our study found remarkably stable results, consistently indicating a positive correlation between the FOI and GDP/HDI. Notably, we successfully replicated this correlation across different search engines (using Baidu instead of Google) and over a span of time (from 2012 to 2021). Consistent with previous studies (Preis et al., 2012), these results added solid evidence to the association between the economic prosperity of a city and the online information-seeking behavior of its citizens. That is, searching more for information about the future (i.e., the following year) rather than the past (i.e., the past year) may indicate a higher level of future orientation, which in turn may contribute to greater economic success. Our results not only justify

the use of online query data as a convenient tool for measuring future orientation, but also serve as an example of how such data can be valuable in capturing country-level psychological states (Lai et al., 2017).

Beyond cross-country comparison, our results suggested the Baidu-FOI may serve as a sensitive index that can effectively capture province-level differences in future orientation in China. While most previous studies have primarily used the FOI as a country-level index (Burro et al., 2022; Preis et al., 2012; Schaub, 2022), our results extend the correlation between the FOI and GDP/HDI from an inter-cultural to an intra-cultural context. In China, although various intra-cultural differences have been identified (e.g., Gong et al. (2021); Talhelm et al. (2014); Zhang et al. (2023)), the intra-cultural differences in future orientation (or long-term orientation) among provinces have not been extensively explored. Here, our results suggested the Baidu-based FOI could be effective and stable to catch the intra-cultural variation of future orientation between China provinces – It could not only reveal the general regional difference (i.e., Eastern China showed higher future orientation than Central and Western China), but also precisely predict the province development (i.e., strong positive correlations between FOI and GDP/HDI). Based on our primary example of using Baidu-based FOI to investigate the intra-cultural differences, researchers in the field of cultural psychology can access the FOI from the open dataset (https://osf.io/ygj76/?view_only=1d98730f60a04588a987f5d25aa987e9) and use it to investigate any related hypotheses.

Besides these successful replications and extensions mentioned above, we argued that our results may contribute to the future research by highlighting the following two prerequisite when using the FOI as a measurement of future orientation:

1) Choose a local dominant search engine and unambiguous keywords to calculate the FOI. Our comparison between the Baidu-based and Google-based FOI pointed out one notable concern for the FOI: the potential sampling bias caused by using a non-dominate search engine (e.g., Google in China or Russia). From our results, the correlation between the FOI and GDP/HDI among China provinces can be heavily distorted (only significant in 2012) when using data from Google Trends as a non-domain search engine. Indeed, prior research has reminded the importance of considering potential disparities between distinct online platforms in the realm of online behavior analysis. For instance, studies have highlighted notable systematic distinctions between Weibo and Twitter as two microblogging services (Gao et al., 2012). Thus, we strongly emphasize the importance of a crucial prerequisite for using the FOI to capture future orientation differences: basing the data on a search engine that is dominant in the respective country. Researchers must remain cognizant of the nuances due to specific search engines and be diligent in choosing a suitable data source (not necessarily Google Trends) to calculate the FOI and exercise caution when interpreting previous results obtained from a potentially biased FOI.

Moreover, another concern of the FOI should be noticed here is its susceptibility to ambiguity, especially when Arabic numerals used in search queries have multiple meanings. For instance, we observed this issue with the searching data in 2012, which can refer to both the calendar year and the popular Hollywood movie titled *2012*. This ambiguity could also lead to biased FOI scores and distorted its relationship with GDP/HDI.

2) As a group-level measurement, the FOI is not appropriate to be used for capturing individual-level future orientation. While the FOI proves to be useful in capturing differences in future orientation at the province (intra-country) level, its ability to predict individual-level variables, such as patience, was found to be weak ($\beta = -.038$). This lack of a significant relationship

between FOI and patience aligns with previous research findings (Burro et al., 2022), and also emphasizes the need for caution when applying the FOI to individual-level contexts. Indeed, negligible correlation with individual-level variables could be a common issue for group-level measurements of future orientation. As noted by Hofstede and Minkov (2013) in their Values Survey Module (another measurement for country-level culture differences), the country-level correlations can differ significantly from individual-level correlations. They even stated that a country-level cultural variable is not suitable and should never be used for comparing individuals. To measure individual-level future orientation, more specific questionnaires or indexed based on individual-level online behaviors need to be developed, e.g., a questionnaire targeted to individual-level cultural values (Yoo et al., 2011), the future sightedness index based on individual's Twitter posts (Thorstad & Wolff, 2018), etc.

The current replications and extensions also warrant consideration of several inherent limitations: 1) The correlation between FOI and GDP/HDI was tested across only one different local search engines (i.e., Baidu). Future research may try to investigate the reliability and validityof the FOI based on more local search engines, such as Yandex or Naver; 2) It's notable that the Baidu-based FOI we used here and the widely utilized Google-based FOI are not directly interchangeable or comparable. Due to the incongruity arises from the distinct calculation methodologies underlying the Baidu Index and Google Trends, these two FOIs are difficult to be applied into one cross- culture research, i.e., research can only choose either Baidu or Google (but not a mix of them) to calculate the FOI. A promising avenue for future research could involve the development of an adjusted algorithm, similar to the approach proposed by Cavalli (2020), aimed at standardizing the FOI derived from disparate search engines while preserving the online query information of each regions at the same time.

5 Conclusion

This study aimed to replicate and extend the findings of Future Orientation Index (FOI) proposed by Preis et al. (2012). Our results provide compelling evidence that the positive correlation between FOI and GDP/HDI reported in Preis et al. (2012) is replicable in China, suggesting the robustness and stability of FOI across search engines (from Google to Baidu), time periods (from 2012 to 2021) and level (from inter-country to intra-country level, but not to individual level). We also highlighted two prerequisites when using the FOI as a measurement of future orientation: 1) Choose a local dominant search engine and unambiguous keywords to calculate the FOI; 2) Apply the FOI into a group-level context (but not individual-level).

6 Supplementary Materials

6.1 The FOI data from 2013

According to the calculation of the FOI, volume of searches of the word "2012" is necessary to obtain the FOI of 2013. However, since the word "2012" was also the name of a famous movie, it's hard to get the volume of searches of "2012" as a year instead of as a movie. Thus, the huge and chaotic volume of searches of "2012" caused the FOI of 2013 distorted from the regular pattern. In detail, compared to the FOI of other years, the FOI of 2013 among all provinces tended to be extremely small (only ranged from 0.204 to 0.427), as the denominator (i.e., the volume of searches of "2012") was relatively larger. From another perspective, the related word of "2012" given by the Baidu Index were mostly related to the movie, e.g., "2012 doomsday", "disaster film", "John Cusack", etc. Considering these facts, we believed the volume of searches of "2012" deviated from its original intention and could not reflect people's focus of the previous year in 2013. Thus, the FOI of 2013 was excluded from our analysis.

6.2 The FOI list from 2012 to 2021

Table S1. The FOI list of each province from 2012 to 2021

Province	Year									Mean
	2012	2014	2015	2016	2017	2018	2019	2020	2021	
Shanghai	1.35	1.07	1.14	1.18	1.56	1.13	1.32	1.25	1.08	1.23
Beijing	1.43	1.01	1.03	1.17	1.40	1.10	1.22	1.19	0.99	1.17
Guangdong	1.18	0.80	0.88	1.08	1.35	1.04	1.18	1.15	0.97	1.07
Tianjin	1.18	0.78	0.87	1.34	1.17	0.94	1.04	0.96	0.96	1.03
Zhejiang	1.19	0.78	0.82	0.99	1.22	0.89	1.01	0.99	0.90	0.98
Liaoning	1.18	0.86	0.78	0.97	1.17	0.94	0.97	0.93	0.88	0.96
Jiangsu	1.16	0.81	0.82	0.95	1.24	0.89	1.03	0.94	0.84	0.96
Chongqing	1.07	0.78	0.81	0.91	1.12	0.93	0.86	0.93	0.87	0.92
Fujian	1.03	0.76	0.82	0.92	1.07	0.84	0.91	0.93	0.81	0.90
Jilin	1.08	0.82	0.75	0.88	1.04	0.92	0.89	0.89	0.83	0.90
Anhui	1.07	0.76	0.71	0.83	1.47	0.79	0.87	0.80	0.71	0.89
Sichuan	1.12	0.80	0.83	0.89	1.03	0.81	0.85	0.81	0.75	0.88
Heilongjiang	1.10	0.83	0.75	0.86	0.90	0.93	0.78	0.84	0.81	0.87
Hubei	1.07	0.77	0.80	0.88	0.99	0.81	0.86	0.81	0.76	0.86
Shandong	1.10	0.81	0.72	0.83	1.02	0.78	0.85	0.79	0.75	0.85
Hainan	0.96	0.71	0.72	0.77	1.08	0.78	0.89	0.85	0.84	0.84
Inner Mongolia	1.03	0.75	0.68	0.78	1.02	0.82	0.86	0.83	0.79	0.84
Shaanxi	1.01	0.75	0.72	0.79	1.05	0.77	0.85	0.81	0.74	0.83
Jiangxi	1.04	0.78	0.73	0.80	1.03	0.80	0.83	0.74	0.72	0.83
Guangxi	1.01	0.72	0.75	0.82	1.00	0.79	0.80	0.79	0.77	0.83
Xinjiang	1.02	0.71	0.71	0.73	1.07	0.69	0.95	0.80	0.78	0.83
Yunnan	1.06	0.73	0.72	0.78	1.09	0.80	0.72	0.80	0.67	0.82
Hunan	1.03	0.75	0.71	0.78	0.97	0.74	0.77	0.75	0.68	0.80
Hebei	1.01	0.69	0.62	0.78	0.97	0.78	0.80	0.76	0.79	0.80
Shanxi	1.00	0.73	0.65	0.72	0.94	0.73	0.75	0.73	0.69	0.77
Guizhou	1.00	0.66	0.66	0.71	1.01	0.72	0.67	0.72	0.67	0.76
Gansu	0.98	0.70	0.65	0.70	0.96	0.67	0.71	0.71	0.69	0.75
Henan	0.93	0.68	0.63	0.75	0.94	0.59	0.75	0.65	0.62	0.73
Ningxia	0.92	0.61	0.58	0.64	0.84	0.65	0.69	0.76	0.72	0.71
Qinghai	0.70	0.60	0.53	0.61	0.90	0.59	0.70	0.86	0.71	0.69
Tibet	0.76	0.46	0.48	0.46	0.87	0.59	0.73	0.60	0.58	0.62
Mean	1.06	0.76	0.74	0.85	1.08	0.81	0.87	0.85	0.79	0.87
CV	0.13	0.14	0.17	0.21	0.16	0.17	0.18	0.17	0.14	0.15

Note: $CV = M / SD$, referring to the coefficient of variation.

6.3 The scatterplots between the FOI and GDP/HDI

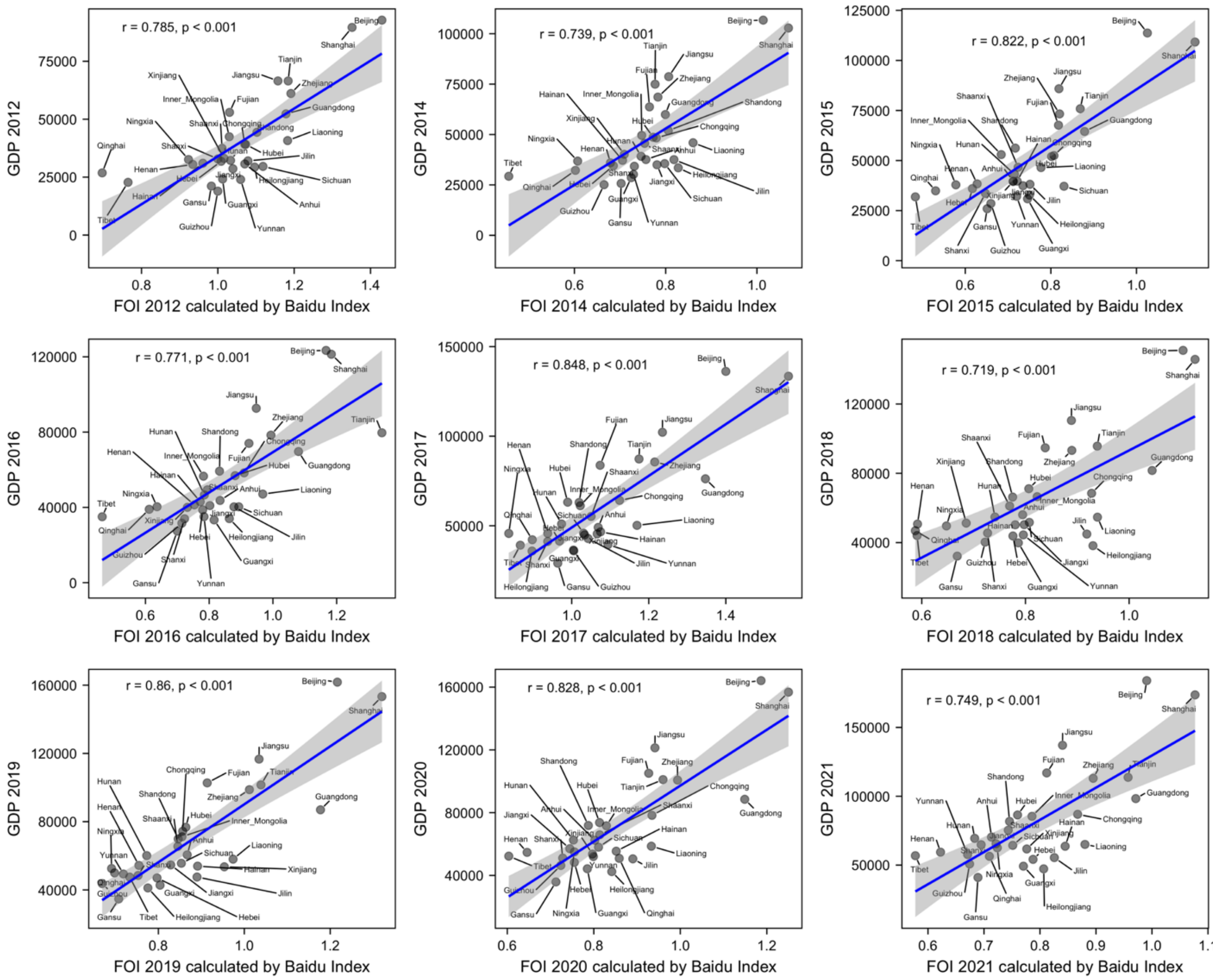

Figure S1. The scatterplots between the FOI and GDP from 2012 to 2021. Each panel represented one single year. Each dot represented a province in China and was labelled by the province name.

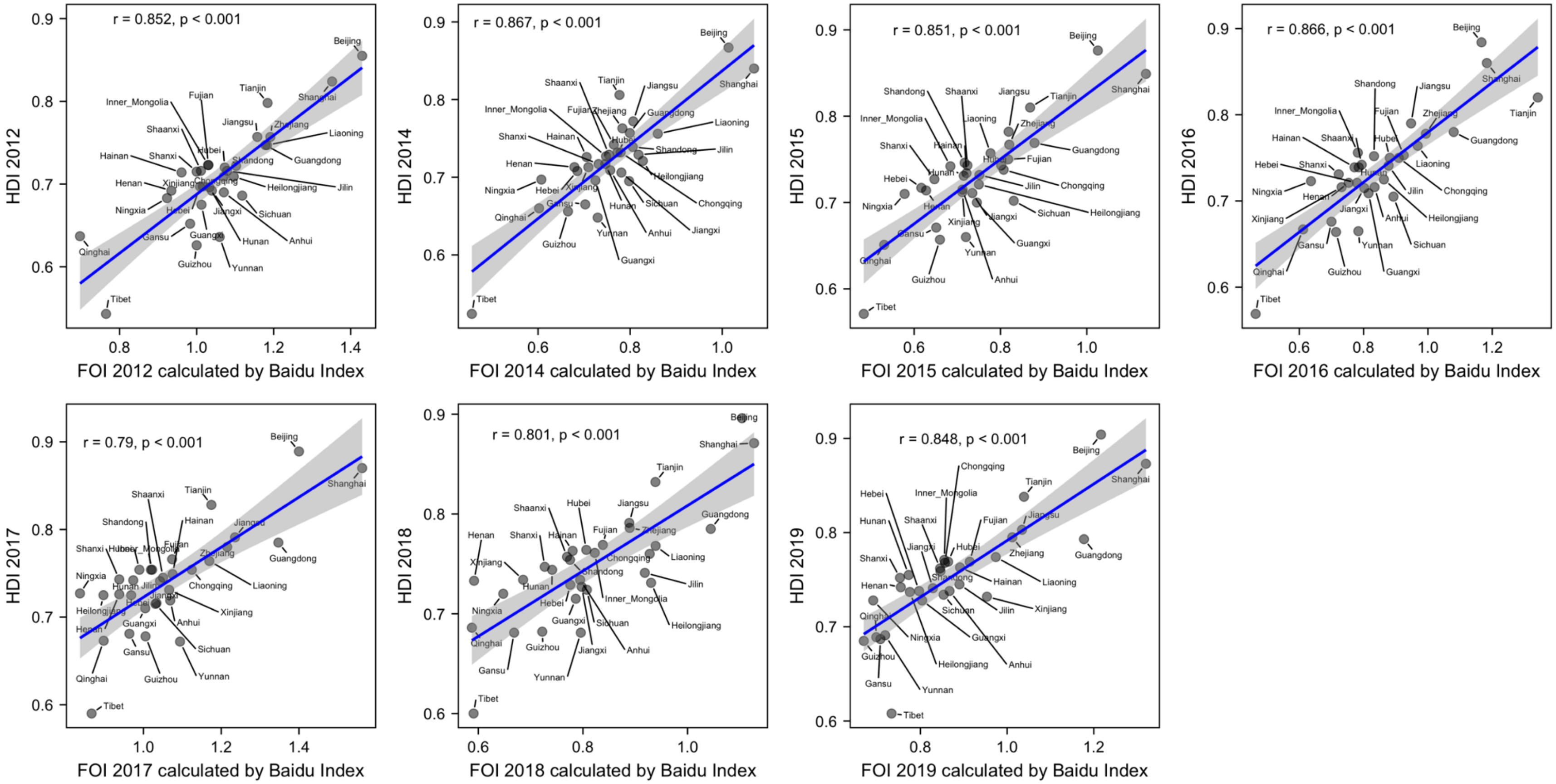

Figure S2. The scatterplots between the FOI and HDI from 2012 to 2021. Each panel represented one single year. Each dot represented a province in China and was labelled by the province name.

6.4 Correlation between the Google-based FOI and GDP / HDI

Table S2. The relationship between the Google-based FOI and GDP/HDI from 2012 to 2021.

Year	*NA*	Google-based FOI and GDP		Google-based FOI and HDI	
		Correlation (r)	Robust regression (β)	Correlation(r)	Robust regression (β)
2012	1	.833***	.833***	.625***	.636***
2014	0	.161	.075	.241	.149
2015	5	.458*	.356	.367*	.423*
2016	3	.008	- .002	- .122	- .045
2017	3	.337	.211	.237	.208
2018	1	- .057	- .034	.029	- .021
2019	1	.221	.180	.130	.050
2020	2	.401*	.205	/	/
2021	3	.298	.212	/	/

Note: *NA* means the number of missing values (the Google Trends did not give any output for that province) for each year. r means the correlation coefficients between the Google-based FOI and GDP/HDI; β means the standardized regression coefficients from the robust regression using FOI to predict GDP/HDI. $p^{***} < .001$, $p^{**} < .01$, $p^{*} < .05$.

6.5 The simple slope analysis of the interaction between the FOI and age

From the hierarchical linear model (the Model 3), the interaction term between the FOI and age was significant better (β = -0.044, p = .026). Then, we conducted the simple slope analysis to obtain the different age effects among provinces with different FOI. The interaction plot (Figure S3) showed the simple slope directly. In detail, when the FOI was above the mean with 1 *SD*, the age effect = -0.119, p < .001; when the FOI was at the mean level, the age effect = -0.074, p = .001; when the FOI was below the mean with 1 *SD*, the age effect = -0.030, p = .316. That is, the negative effect of age on patience was greater in the province with a higher FOI.

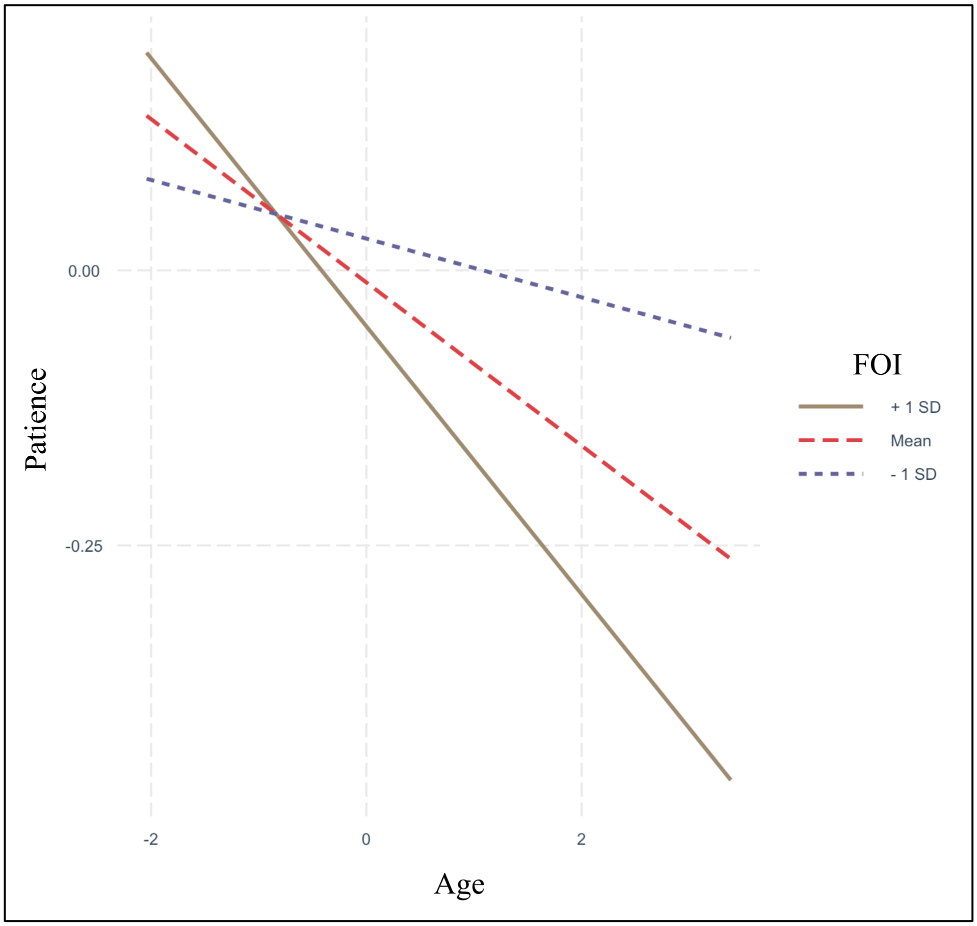

Figure S3. The simple slope plot of the interaction between the FOI and age. Different lines represented different levels of FOI (i.e., mean, above and below one *SD*). All the variables (patience, age, and FOI) were standardized.

7 Reference

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